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AUTHOR Carr, Sonya C.
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ABSTRACT

This paper briefly explains the possible two-mode techniques of factor analysis and discusses in more detail one two-mode technique, the Q-technique, which may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. A concrete heuristic example is used to illustrate Q-technique factor analysis. In this example, the effects of various data-collection strategies on Q-technique factor analytic results are investigated. Nine faculty members of a special education department of a large, urban university responded to 69 statements taken from an attitudes toward disabilities scale. Data were collected three times using different strategies: conventional Q-sort; mediated-ranking; and an unmarked graphic scale. The three data sets were then factor analyzed to determine the clusters or factors of subjects across the variable replicants. Principal components analysis was used to extract factors and the factors were rotated using the varimax procedure. The use of factor scores to facilitate interpretation of person factors is also illustrated. It is concluded that there are times when it is important to be concerned with clusters of people, rather than clusters of variables, and data-collection strategies should be used that facilitate meaningful interpretation. In such a case, the mediated-ranking strategy may be preferable to other data-collection strategies. Twelve data tables and four figures are provided. (Author/TJH)

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Effects of Different Data Collection Strategies on Q-Technique Factor Analytic Results

Sonya C. Carr

University of New Orleans 70148

Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA, March 30, 1989.

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Abstract

This paper briefly explains the possible two-mode techniques of factor analysis and discusses in more detail one two-mode technique, Q-technique, which may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. A concrete heuristic example is used to illustrate Q-technique factor analysis. In this example, the effects of various data-collections strategies on Q-technique factor analytic results are investigated. Nine faculty members of a special education department of a large, urban university responded to 69 statements taken from an attitudes toward disabilities scale. Data were collected three times using different strategies: conventional Q-sort, mediated-ranking, and an unmarked graphic scale. The three data sets were then factor analyzed to determine the clusters or factors of subjects across the variable replicants. Principal components analysis was used to extract factors and the factors were rotated using the varimax procedure. The use of factor scores to facilitate interpretation of person factors is also illustrated.

Effects of Different Data Collection Strategies on Q-Technique Factor Analytic Results

Factor analysis is an analytic technique commonly used to examine the interrelationships among variables. Factor analysis may be used as an exploratory technique to identify underlying constructs and thus elaborate theory. Or factor analysis may be used as a reductive technique to condense a large number of variables into a smaller number of "underlying" variables which retain most of the information in the larger, original variable set; these scores are then employed in subsequent substantive applications.

Before the effects of different data collection strategies on Q-technique factor analytic results are explained and illustrated here, some issues more generally relevant to factor analytic design will be presented. Cattell (1966) discussed possible techniques of relational analysis in the behavioral sciences, and proposed a Basic Data Relation Matrix or "data box" to conceptualize the available techniques. Based on this notion of a "data box," three aspects, subjects, variables, and occasions or times of measurement, can be used to characterize the data in a study. While it is possible to design studies in which all three dimensions are investigated (e.g., Thompson & Miller, 1978), typically researchers investigate only two dimensions, while the third is held constant. Therefore, six possible two-mode techniques of factor analysis have been delineated from the

combinations of data aspects.

Typically in factor analysis a two-dimensional data matrix is analyzed with the columns of the matrix representing different variables and the rows incorporating the scores of individuals on those variables. Thus, the analysis is based on correlations among variables computed across individuals, and represents what Cattell (1966) labelled R-technique factor analysis. Factor analysis may also be used to examine correlations among people computed across variables, and this analysis is called Q-technique. When the two modes to be analyzed are variables and occasions of measurement, correlations can be computed among variables across occasions of measurement, with the subject of the study being a single person or data object, and this is termed P-technique factor analysis. Or correlations can be computed among occasions across a series of variable scores, and this is termed O-technique factor analysis. When the two modes to be analyzed are individual subjects and occasions of measurement, with the variable held constant, correlations can be computed between occasions across a sample of individuals, and this is called T-technique factor analysis. Or correlations can be computed between subjects across a series of occasions of measurement of a single variable, and this is called S-technique factor analysis.

The present paper focuses on various data collection strategies which can be used for Q-technique factor analysis. Kerlinger (1986) described Q-technique as "a sophisticated

way of rank-ordering objects (items, stimuli, etc.) and then assigning numerals to subsets of the objects for statistical purposes" (p. 507). Q-technique has been referred to as "inverse" analysis (Comrey, 1973) and as "transposed" or "inverted" analysis (Nunnally, 1967).

Stephenson (1953), in a seminal work in the literature on Q-technique, discussed applications of Q in the study of personality, social psychology, and clinical psychology. He proposed that it may be more important to examine relationships among people rather than relationships among variables. Q-technique may be helpful, for example, in investigating clusterings of people based on variables such as attitudes, preferences, or thinking behavior. Kerlinger (1986) suggested that Q-technique could be used to open up new research areas, to explore hunches, and to test preliminary theories. In Q "one tests theories on small sets of individuals carefully chosen for their 'known' or presumed possession of some significant characteristic or characteristics. One explores unknown and unfamiliar areas and variables for their identity, their interrelations, and their functioning" (Kerlinger, 1986, p. 521).

More recently, Thompson (1980a) used Q-technique to investigate the validity of a fourfold typology of evaluators. Professional evaluators in a school district were categorized by their immediate superiors as one of four types of evaluators: Technicians, Politicians, Entrepreneurs, or Pretenders. Each evaluator then

participated in a modified Q-sort task in which they rank ordered statements identified as characteristics of this theory's specifications of evaluator types. A Q-technique factor analysis was employed to evaluate the theory and the correspondence of supervisors' perceptions with the data provided by the evaluator subjects.

Similarly, Townsend (1987) investigated the manner in which faculty, medical librarians, media producers, and instructional designers make decisions about the types of media to be used in medical education. He developed, validated and revised a Media Selection Inventory using R-technique factor analysis. Townsend then had various individuals representing these same functions in professional education respond to the revised Inventory and he analyzed their responses using Q-technique factor analysis. In summary, the use of Q-technique to study human behavior seems to have wide application.

Q-Technique Data Collection

Typically, Q-technique involves a sorting procedure, called a Q-sort, and the correlation of responses of individuals to the Q-sorts. Stimuli sampled from a specifible universe of content are given to a subject for sorting. The subject is directed to sort the set of objects (e.g., verbal statements, single words, phrases, or pictures) by putting varying numbers of cards or stimuli into several piles between two extremes. The number of cards to be assigned to each pile is based on a predetermined symmetrical

distribution. Thus, a rank-order continuum is developed with extremes labeled, for example, "Most Approve" to "Least Approve," "Most Like Me" to "Least Like Me," or "Prefer Most" to "Prefer Least." Because subjects are required to distribute their responses in terms of a fixed distribution, usually an approximately normal distribution, all subjects will have exactly the same mean rating, the same standard deviation of ratings, and the same distribution of ratings. Thus, relationships of persons' score profiles will not be attenuated by score distribution differences, since the distributions will be identical for each person.

Typically a Q-sort may contain 60-120 cards. Kerlinger (1986) recommends that at least 60 cards be used for statistical stability and reliability. In Q-technique the columns of the data matrix contain information about the individual's scores or responses to statements/items while the rows represent the statements or items. Thus, in Q-technique factor analysis, the persons have factor loadings and the variables have factor scores. It is important to note that for meaningful analysis there must be appreciably more replicants (statements/items) than factored entities (persons).

When a Q-sort is used, it is also important to consider how the stimuli to be sorted are selected. Instead of a sampling of people, the researcher is concerned with a sampling of stimuli. While it seems clear that all stimuli need to come from some common frame of reference, Nunnally

(1967) asserts that there are problems in defining "populations" of stimuli.

One way in which the researcher can generate a structured sample of items is to use the variables of a "theory" or hypothesis in selecting the items to be included. In this approach the "theory" the researcher wishes to test is built into the Q-sort. The Thompson (1980a) study provides an example of the way in which Q-technique can be used to test theory using a structured sample of sorted stimuli.

If it is difficult to generate a sensible structured sample, the researcher may "randomly sample" the desired number of things to be used in a Q-sort. When random samples are used, this method is called an unstructured Q-sort. Kerlinger (1986) defined an unstructured Q-sort as "a set of items assembled without specific regard to the variables or factors underlying the items" (p. 511). In an unstructured Q-sort a large number of items are selected that are assumed to measure one broad variable, for example, attitudes toward the handicapped. Given a theoretically infinite population of items, the hope is that the researcher will select a set of items for the Q-sort that are a representative sample of the item population (Kerlinger, 1986, p. 512). Kerlinger reports that this approach has dominated Q studies.

In addition to difficulties in obtaining a representative sample of the item population for the Q-sort, other criticisms or weaknesses have been attributed to

conventional data-collection methods for Q-technique. When a Q-sort is used, piles or groups of items/objects are rank-ordered according to some criterion. This method has been dominant in applications of Q-technique because it enables the rater to judge a larger number of sample items. As Nunnally (1967) noted, the task of rank-ordering 50-100 items would be extraordinarily time-consuming and tedious. Thus, conventional Q-sort tasks allow the researcher to obtain relatively precise rankings of large sets of stimuli without completely overwhelming subjects.

However, other choices for collecting data to be used in Q-technique analyses are available to the researcher. For example, Thompson (1980b) compared the conventional sorting strategy to a mediated-ranking strategy in an application of Q-technique factor analysis. In this study, subjects were first asked to sort cards across categories in the conventional manner and then to rank the cards within each category. Breaking the task of rank-ordering stimuli into smaller discrete steps makes the task cognitively manageable for subjects. Thompson took the position that a mediated-ranking data-collection procedure enabled the researcher to collect data with more systematic variance and thereby to identify more reliable factors.

A third possible strategy for data-collection with Q-technique factor analysis involves use of an unmarked graphic scale (Thompson, 1981). In Townsend's (1987) study, subjects responded to a questionnaire by marking their response to

each of 44 items on an unmarked graphic scale. The unmarked graphic scale responses for the 44 inventory items were then rank ordered for each individual. Q-technique factor analysis was then performed and factor scores were obtained. Figure 1 illustrates the presentation of an unmarked graphic scale.

INSERT FIGURE 1 ABOUT HERE.

Q-technique may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. Factor analysis then allows the researcher to derive factors or clusters of people, as against the R-technique clustering of variables. The most serious criticism of Q-technique involves the loss of information which results when a conventional data-collection strategy, the Q-sort, is used. However, other data-collection strategies, specifically, a mediated-ranking strategy or an unmarked graphic scale, may be used to obtain more information about levels of differences between individuals. Thus, the purpose of the present study was to illustrate the use of Q-technique generally, and the use of the conventional-sorting strategy, the mediated-ranking strategy, and the unmarked graphic scale more particularly.

A Heuristic Example

A concrete heuristic example may be useful to illustrate various data collection strategies for Q-technique factor analysis. The subjects (n=9) were on the faculty of the

special education department of a large urban university. Each subject responded to 69 statements taken from the Disability Factor Scale-General. This rating scale was developed by Siller (1969) to measure attitudes toward specific disablities. The types of disabilities included on this scale are amputation, blindness, heart trouble, deafness, epilepsy, cancer, paralysis, scarring, and hunchback. This scale was designed for respondents to express their level of agreement or disagreement with each statement using a likert-type format with ratings from "1" (Strongly Agree) to "6" (Strongly Disagree). Siller (1984) has reported seven factorially-defined attitude dimensions for the DFS-G: Interaction Strain, Rejection of Intimacy, Generalized Rejection, Authoritarian Virtuousness, Inferred Emotional Consequences, Distressed Identification, and Imputed Functional Limitations. Internal consistency coefficients for the DFS-G are reported to range from +.73 (Imputed Functional Limitations subscale) to +.87 (Distressed Identifiation subscale) (Siller, 1969, 1970).

This instrument is one of six major scales measuring general attitudes toward people who are disabled, as discussed by Antonak and Livneh (1988). Antonak and Livneh provide specific technical information about each of these scales, and report acceptable reliability and validity coefficients for the Disability Factor Scales.

Subjects in the present study were randomly assigned to one of three groups for the purpose of counterbalancing the

order of the three strategies used for data collection. The members of each group were individually administered the 69 items of the instrument over three sessions spaced two to six days apart. Thus, group 1 used the mediated-ranking data collection strategy during session 1, the conventional data collection method during session 2, and the unmarked graphic scale during session 3. Group 2 used the conventional data collection strategy during session 1, the unmarked graphic scale during session 2, and the mediated-ranking data collection strategy during session 3. Group 3 completed the unmarked graphic scale during session 1, the mediated-ranking data collection strategy during session 2, and the conventional data collection strategy during session 3.

When the unmarked graphic scale was used, responses to items were rank ordered for each individual. Each mark on the scale was given a rank with the item marked closest to "Strongly Disagree" receiving a score of 1 while the item marked closest to "Strongly Agree" received a score of 69. When the conventional-sorting method was used, each subject's data were scored according to the category into which each statement was sorted (scores 1-9). When the mediated-ranking strategy was used, each subject's data were scored for rank-order (scores 1-69). Thus, each individual responded to the same 69 items using three different data-collection strategies. The three data sets were then factor analyzed.

Results and Interpretation

Table 1 presents the correlation matrix among all nine

subjects across the profile of variables for the mediated-ranking strategy. An examination of the correlation matrix shows that more than half of the coefficients are greater than 0.3 in absolute value. Therefore, it seems likely that some of the subjects can be clustered into subsets.

INSERT TABLE 1 ABOUT HERE.

Following the calculation of the correlation matrix, the next step in factor analysis is the initial extraction of common factors. Principal components analysis was used to extract factors from the correlation matrix. In principal components analysis, an assumption is made that the reliability of each factored entity is one or close to one. Therefore, the principal components are extracted from a correlation matrix with ones on the diagonal, a reflection of the presumption of perfectly reliable measurement. In the present analysis factors with eigenvalues close to or greater than one were extracted. The first factor accounted for 65% of the total variance among people. The second factor had an eigenvalue of .96385 and accounted for an additional 10.7% (.96/9) of the variance. Thus, the two extracted factors explained 75.7% of the total variance among the nine subjects. The coefficients in the factor matrix are called pattern coefficients and indicate how much weight each person was assigned in relation to each factor. Because the estimated factors are uncorrelated ("orthogonal"), these pattern coefficients are also the correlations between the variables and each factor, and are also called structure

coefficients.

In order to improve the interpretability of the factors derived from the data, factors were rotated using the varimax procedure. Table 2 presents the factor matrix after varimax rotation. Interpretation of the rotated factor matrix suggests that five of the subjects (PM2, PM5, PM8, and PM9 versus PM4) are close to being "pure" types as defined by the two factors presented in Table 2. It is also possible to plot the persons using the factor structure coefficients as coordinates, to assist in interpretation. If simple structure is achieved, clusters of people should occur at the end of the axes of the pair of factors. An examination of Figure 2 suggests that five of the nine subjects (PM1, PM2, PM5, PM8, and PM9) appeared highly related to Factor I, while one subject (PM4) appeared highly and "univocally" related to Factor II. The remaining subjects (PM3, PM6, and PM7) appear to share characteristics of both person types.

INSERT TABLE 2 AND FIGURE 2 ABOUT HERE.

Table 3 presents the correlation matrix among all nine subjects across the profile of variables for the unmarked graphic scale data-collection procedure. A principal components analysis was used to extract factors from this correlation matrix. In this analysis two factors were extracted. The first factor accounted for 64.8% of the total variance among people. The second factor had an eigenvalue of .87987 and accounted for an additional 9.8% (.87/9) of the variance. The two extracted factors explained 74.6% of the

variance among the nine subjects. With a two-factor solution, after varimax rotation, as reported in Table 4, only three of the subjects (PU4, PU5, and PU9) are close to being "pure" types as defined by the two factors. Interpretation can be facilitated by examining a plot of structure coefficients,and this plot is presented in Figure 3. Two of the nine subjects (PU5 and PU9) appeared highly related to Factor I, while one subject (PU4) appeared highly related to Factor II. The remaining six subjects (PU1, PU2, PU3, PU6, PU7, and PU8) appear to share characteristics of both person types.

INSERT TABLES 3, 4 AND FIGURE 3 ABOUT HERE.

Table 5 presents the correlation matrix among all nine subjects across the profile of variables for the conventional sorting strategy. A principal components analysis was used to extract factors from this correlation matrix. In this analysis two factors were extracted. The first factor accounted for 57.6% of the total variance among people. The second factor had an eigenvalue of .81362 and accounted for an additional 9.0% (.81/9) of the variance. The two extracted factors explained 66.7% of the variance among the nine subjects. With a two-factor solution, after varimax rotation, as reported in Table 6, only two of the subjects (PC4 and PC5) are close to being "pure" types as defined by the two factors. Interpretation can be facilitated by examining a plot of structure coefficients, and this plot is presented in Figure 4. Only one of the nine subjects (PC5)

appeared highly related to Factor I, while one subject (PC4) appeared highly related to Factor II. The remaining seven subjects (PC1, PC2, PC3, PC6, PC7, PC8, and PC9) appeared to share characteristics of both person types.

INSERT TABLES 5, 6 AND FIGURE 4 ABOUT HERE.

Discussion

Thus, when consideration is given to how comparable the groupings of subjects are for each of the data-collection strategies, Subject 5 is consistently identified with Factor I and Subject 4 is consistently identified with Factor II. Although a relatively homogeneous group of subjects was selected so that differences relative to various data-collection strategies would emerge, only when more information is obtained, via the mediated-ranking strategy, is it possible to further identify person types for the other subjects. This is perfectly sensible, since more variance is present in these data, and only in this strategy are subjects consciously aware that they are providing rank-order data with no ties.

While the mediated-ranking strategy provided more information and allowed clusters of persons to more clearly emerge, this procedure is time-consuming and may be tedious for the subject if large numbers of items/statements are used. It might, therefore be of interest to compare the results obtained with the mediated strategy with each of the other strategies. Table 7 presents the correlation coefficients for the subjects over the data-collection

methods. These correlation coefficients can be inspected to determine how well the results of the unmarked graphic scale procedure or the conventional-sorting procedure correlate with the results of the mediated-ranking procedure. Moderate to high correlation coefficients are observed for all methods.

INSERT TABLE 7 ABOUT HERE.

The mean squared $\underline{r}$ (+.589) between data involving the mediated sort (scored 1-69) and the unmarked graphic scale (scored 1-69) was slightly larger than values across other pairs of data collection strategies. These coefficients also tended to be most homogeneous (SD=.112). These results suggest that the mediated-ranking procedure may have utility in generating more systematic variance.

Further interpretation of Q-technique results is facilitated by obtaining factor scores. With principal components analysis, mathematically exact factor scores can be obtained. Table 8 presents the factor scores obtained from the two-factor principal components analysis for the mediated-ranking strategy. Tables 9 and 10 present the factor scores obtained from the two-factor principal components anlysis for the unmarked graphic scale and the conventional-sorting strategy, respectively.

INSERT TABLES 8, 9, AND 10 ABOUT HERE.

The factor scores presented in Table 8 will be used to illustrate the procedure by which factor scores can be consulted to determine which statements provide a basis for

defining and differentiating clusters of subjects. Table 11 presents the most relevant statements and factor scores. Statements with a high positive score indicate strong agreement, and statements with a high negative score indicate strong disagreement. The subjects who clustered on Factor I appear to share a generally positive attitude toward persons with disabilities, and at the same time display a strong awareness of the potential difficulties experienced by handicapped individuals and an empathetic, "helping" attitude. The subject who appears to be a "prototype" for Factor II, Subject #4, seemed to be primarily concerned with the impact of a disability on himself or a loved one. As the third column of Table 11 indicates, the subjects clustering on Factor I differed most from the subject on Factor II with regard to the feeling that the individual could make a good adjustment if he or she became disabled and acceptance of intimacy with a disabled person.

INSERT TABLE 11 ABOUT HERE.

Table 12 presents correlation coefficients for the factor scores over data collection procedures. An examination of this table indicated that factor scores obtained for responses using the mediated-ranking strategy are more highly correlated with factor scores for the unmarked graphic scale procedure than with factor scores for the conventional-sorting strategy. It should be noted that all of the factor scores for the three data-collection strategies are moderately to highly correlated.

INSERT TABLE 12 ABOUT HERE.

Summary

Q-technique factor analysis is used to examine correlations among people computed across variables. Q-technique has been used to investigate clusterings of people based on variables such as attitudes, preferences, and thinking behavior. With Q-technique factor analysis it is possible to obtain factors which can be thought of as idealized "types" of persons. Typically, a Q-sort is used to collect data for Q-technique factor analysis. However, the Q-sort is an ipsative, forced-choice procedure, and important information regarding levels differences between individuals may be lost. Alternative data-collection methods, specifically, a mediated-ranking strategy and an unmarked graphic scale strategy, have been proposed. In this example, data were collected from the same subjects using each of three strategies. The results indicate that when Q-technique factor analysis is used to obtain information about "types" of individuals with regard to certain attitudes, the mediated-ranking strategy provides the most meaningful outcome. Thus, there are times when it is important to be concerned with clusters of people, rather than clusters of variables, and data-collection strategies should be used which facilitate meaningful interpretation. The mediated-ranking strategy, as illustrated here, may be preferable to other data-collection strategies.

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Table 1

Correlation Matrix for Mediated-Ranking Strategy

	PM1	PM2	PM3	PM4	PM5	PM6	PM7	PM8
PM1	--							
PM2	.69291	--						
PM3	.60727	.64596	--					
PM4	.24541	.26383	.43796	--				
PM5	.62400	.75323	.54030	.24596	--			
PM6	.62791	.72587	.60705	.41414	.69974	--		
PM7	.66628	.76682	.67790	.37296	.71768	.72254	--	
PM8	.60643	.75904	.53117	.25882	.78520	.66916	.63518	--
PM9	.66039	.69043	.51374	.25817	.69558	.69609	.69313	.70563

Table 2

Rotated Principal Components Factor Matrix

	FACTOR 1	FACTOR 2
PM1	.78585	.20165
PM2	.87879	.19901
PM3	.60110	.55705
PM4	.08869	.94826
PM5	.87423	.12177
PM6	.77036	.38889
PM7	.79561	.36803
PM8	.85717	.11642
PM9	.83938	.14460

Table 3

Correlation Matrix for Unmarked Graphic Scale

	PU1	PU2	PU3	PU4	PU5	PU6	PU7	PU8
PU1	--							
PU2	.75320	--						
PU3	.59478	.59003	--					
PU4	.48933	.53785	.62360	--				
PU5	.56463	.66533	.41662	.35835	--			
PU6	.65356	.62832	.60201	.60665	.71286	--		
PU7	.68524	.65294	.64351	.53095	.65137	.64626	--	
PU8	.72262	.71794	.57494	.46427	.74571	.74534	.74859	--
PU9	.61213	.62901	.45374	.32985	.59072	.49277	.54940	.59675

Table 4

Rotated Principal Components Factor Matrix

	FACTOR 1	FACTOR 2
PU1	.70597	.46727
PU2	.73235	.45253
PU3	.34414	.79808
PU4	.16565	.89557
PU5	.85919	.17972
PU6	.62847	.56900
PU7	.66654	.52547
PU8	.80966	.38983
PU9	.79479	.14704

Table 5

Principal Components Correlation Matrix
for Conventional-Sorting Strategy

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
PC1	--							
PC2	.55804	--						
PC3	.55357	.63393	--					
PC4	.38393	.38393	.43750	--				
PC5	.42857	.45089	.37500	.21875	--			
PC6	.32143	.49107	.51339	.39732	.40179	--		
PC7	.63393	.74554	.78571	.58036	.48214	.63393	--	
PC8	.47321	.62500	.59821	.37500	.40625	.36161	.56696	--
PC9	.50446	.67857	.54464	.52232	.56250	.53571	.74554	.58036

Table 6

Rotated Principal Components Factor Matrix

	FACTOR 1	FACTOR 2
PC1	.61715	.38514
PC2	.68698	.48182
PC3	.52605	.62556
PC4	.04003	.87052
PC5	.84764	.00245
PC6	.38325	.58745
PC7	.58515	.71956
PC8	.63612	.39687
PC9	.64820	.53640

Table 7

Correlation Coefficients for Data Collection Methods

		Mediated X Unmarked		Mediated X Conventional		Unmarked X Conventional	
Subject	Order	r	r^2	r	r^2	r	r^2
1	1	0.70	0.48	0.64	0.41	0.73	0.53
2	1	0.79	0.63	0.82	0.67	0.77	0.59
3	1	0.69	0.47	0.73	0.54	0.82	0.66
4	2	0.76	0.58	0.48	0.23	0.57	0.32
5	2	0.79	0.63	0.65	0.42	0.70	0.48
6	2	0.92	0.84	0.79	0.62	0.76	0.58
7	3	0.82	0.66	0.84	0.71	0.77	0.60
8	3	0.70	0.49	0.64	0.41	0.53	0.28
9	3	0.72	0.51	0.87	0.76	0.69	0.47
Order #1	Mean	0.528		0.538		0.594	
	SD	0.073		0.106		0.056	
Order #2	Mean	0.683		0.423		0.460	
	SD	0.112		0.158		0.106	
Order #3	Mean	0.555		0.626		0.448	
	SD	0.078		0.154		0.130	
TOTAL	Mean	0.589		0.529		0.501	
	SD	0.112		0.164		0.121	

Table 8

Principal Components Factor Scores for Mediated-Ranking Strategy

SEQ	FSMED1	FSMED2
1	-.24291	-.18192
2	1.06394	-.20912
3	-1.66884	-.86446
4	-.00801	-1.19520
5	-1.13004	-1.04275
6	1.34561	.47498
7	1.79653	-1.67361
8	1.82094	-.83033
9	-.67916	.52757
10	-1.45272	-1.43113
11	-.57235	-.90642
12	-.94641	1.85505
13	.04168	1.36716
14	-.14579	.64698
15	1.71171	.67022
16	-.37231	.27341
17	-1.16798	-.51541
18	.82073	-.50635
19	-.82207	.40946
20	-.66392	-.26643
21	-.41785	1.40819
22	-.14912	-.53660
23	.37261	1.68475
24	-1.33177	-1.00875
25	1.04998	.84606
26	-.60435	1.63413
27	1.06959	1.18077
28	-.76984	-1.11575
29	.61018	-.81133
30	-.56172	.31981
31	-1.50938	-.65850
32	-.51078	.08041
33	-.12725	-.05164
34	-1.18903	1.74407
35	-1.34860	.04224
36	1.69968	-.17707
37	.18065	-1.09512
38	-.84391	1.74406
39	-1.86124	-.31148
40	-.75319	-.38858
41	1.09672	-1.36826
42	1.22749	.68828
43	1.48131	1.08229
44	1.18975	-.95572
45	.05786	1.02905
46	-1.15316	.65762

SEQ	FSMED1	FSMED2
47	.62665	.71053
48	-.18083	.42806
49	.49150	.08825
50	.96476	.34848
51	-.87274	1.18288
52	-1.18979	-.97717
53	.45663	-1.93131
54	.08479	.96778
55	.71776	-1.67780
56	1.72822	.14043
57	.58231	.42370
58	1.74294	-1.85572
59	-.80452	.04563
60	.12843	-.89915
61	.51676	1.33696
62	-.22282	-.14345
63	-.07834	.07440
64	-1.60067	-.27546
65	1.15348	.79985
66	.74902	-.18032
67	-.59917	-.98098
68	.52277	1.68347
69	-.55034	-1.57366

Table 9

Principal Components Factor Scores for Unmarked Scale

SEQ	FSUN1	FSUN2
1	-.67020	-.05106
2	.05230	1.70539
3	-1.64640	-.96362
4	.43941	-1.24723
5	-.79228	-1.21092
6	1.44846	.31989
7	1.86141	-1.03275
8	2.16187	-.37491
9	-.56662	-.19751
10	-1.64486	-.98248
11	.03740	-1.46146
12	-.02442	.99588
13	.33671	.80210
14	-1.34754	.74678
15	1.63547	.89869
16	-.40977	-.24881
17	-1.27017	-.94850
18	.73161	.69687
19	-1.26456	1.44443
20	-.38909	-1.17112
21	-1.10830	1.73457
22	-.01825	-.70899
23	.43964	1.23272
24	-1.30454	-.68482
25	.49150	1.01459
26	-1.07115	2.04342
27	1.54020	1.19930
28	.29596	-1.81798
29	.05269	.69945
30	-.51782	-.13250
31	-1.25354	-.78052
32	-.05271	-.37250
33	-.71826	.17113
34	-.13014	-.01534
35	-.85784	-.33055
36	1.76967	.37025
37	.65602	-1.46530
38	-1.20553	1.35838
39	-.87463	-1.43392
40	-1.30689	.08977
41	1.66783	-1.03205
42	1.17293	.84022
43	1.37670	1.40012
44	1.23244	-.99537
45	-.14427	1.33396
46	-1.27426	.05993

SEQ	FSUN1	FSUN2
47	-.05378	1.28627
48	.60065	.23306
49	.18144	.45829
50	.97515	.51177
51	-.39192	-.20390
52	-.87688	-.55105
53	.59212	-1.72140
54	-.10141	-.03248
55	1.09229	-1.38830
56	1.31907	.54579
57	-.53154	.59334
58	1.95659	-1.52693
59	-1.10528	-.46607
60	-.06353	-1.09145
61	-.23952	.81677
62	-.94814	.92516
63	-.20855	.49318
64	-1.00060	-1.21108
65	1.51494	.55140
66	.09126	.74866
67	-.19678	-1.39691
68	.06340	1.15534
69	-.20521	-.22706

Table 10

Principal Components Factor Scores for Conventional-Sorting Strategy

SEQ	FCON1	FCON2
1	.00618	-.26966
2	1.34903	-.21626
3	-.94819	-1.95249
4	.28453	-.79756
5	-.08849	-1.36664
6	.88352	1.46662
7	1.35659	-.78256
8	1.26695	.87050
9	.25901	-.47521
10	-1.18177	-1.65550
11	.43742	-1.65036
12	-1.79922	2.20747
13	.27098	.44102
14	-.96520	1.02421
15	-.45565	2.53611
16	-.76460	.15430
17	-.79668	-1.14070
18	.44360	.95710
19	.27606	-.79111
20	-1.12222	-.29153
21	.59297	-.24032
22	-.13031	.17069
23	-.19808	1.33113
24	-.88321	-1.71179
25	.68599	.84557
26	-.31379	1.01863
27	1.82759	1.31416
28	.47168	-1.09001
29	.17631	.01715
30	-.90229	.32611
31	-2.24905	.15098
32	.16660	.21269
33	-.26984	.04415
34	.40960	-.45452
35	-1.09289	-.03889
36	1.80281	.66933
37	.45644	-.59240
38	-.89165	.72941
39	-1.19964	-2.02973
40	-.59727	-.60166
41	.80441	-.32484
42	.15138	1.69982
43	1.38597	1.53968
44	.87687	-.23039
45	-.44411	1.12721
46	-.82783	.28849

SEQ	FCON1	FCON2
47	.99313	-.10083
48	.75423	-.21319
49	.82157	-.03053
50	1.06144	.06074
51	-.68254	.00673
52	-1.79093	-.26826
53	-.26116	-.66935
54	.45422	-.35037
55	.04163	-.35261
56	1.14893	1.26072
57	-.28549	.36028
58	2.07280	-1.77340
59	-1.65964	.17426
60	-.37950	-.45215
61	.79574	-.45737
62	-.56954	-.38473
63	-1.23397	1.47870
64	-1.46943	-.50434
65	2.21946	.21541
66	-1.53017	1.72751
67	.18561	-1.57392
68	1.09425	-.19867
69	-.30114	-.39301

Table 11

Factor Scores on the Statements Which Defined and Differentiated the Clusters

Agree/Disagree	Statement	Score for Item		
	Factor I	I	II	I-II
AGREE				
	*I think if I became blind I could make a pretty good adjustment.	1.80	-1.67	3.47
	*Hunchbacks are as capable as anyone.	1.82	-.83	2.65
	When I know a child is deaf, I feel especially warm toward him.	1.19	-.96	2.15
	*A person missing an arm or leg can function well with an artificial limb.	1.70	-.18	1.88
	*With today's drugs, epilepsy is not a serious condition.	1.73	.14	1.59
	When I see a blind person, I try to imagine what it is like to be blind.	.82	-.51	1.33
	I would never adopt a child who is paralyzed.	1.06	-.21	1.27
DISAGREE				
	Because a blind person can't see me, he could never really know me.	-1.15	.66	1.81
	I feel that a person with a hunchback must have done something to deserve it.	-1.86	-.31	1.55
	Blind people and normal people can't really understand each other.	-1.35	.04	1.39
	Paralyzed people ought to be kept apart from the normal community.	-1.60	-.28	1.33
	Most people who are paralyzed feel bitter.	-.82	.41	1.23
	I would be unhappy if a friend of mine thought of marrying a person who has epilepsy.	-.68	.53	1.21

* Agreement with these statements reflects a positive attitude. Disagreement with the remainder of the statements indicates a positive attitude toward disabled people.

Factor Scores on the Statements Which
Defined and Differentiated the Clusters

Agree/Disagree	Statement	Score for Item		
	Factor II	I	II	I-II
AGREE				
	I would rather be dead than be paralyzed.	-1.19	1.74	2.93
	People with cancer are often angry at the world.	-.95	1.86	2.80
	Even if I fall in love with a person who has cancer, I don't think I would marry him/her.	-.84	1.74	2.59
	If I were a hunchback I would feel like hiding and avoiding people.	-.60	1.63	2.24
	I wouldn't let myself fall in love with a person who is missing a limb.	-.87	1.18	2.06
	If I were missing an arm or leg I would feel like hiding and avoiding people.	-.42	1.41	1.83
	I am sometimes afraid that I will become paralyzed.	.52	1.68	1.60
	Sometimes I am afraid of getting badly scarred.	.04	1.37	1.33
	I would never adopt a child who is blind.	.37	1.68	1.31
DISAGREE				
	*I would date a blind person as readily as I would anyone else.	1.74	-1.86	3.60
	*If I lost an arm or leg, I think I would make a good adjustment.	1.10	-1.37	2.46
	*I think if I became paralyzed I would make a pretty good adjustment.	.72	-1.68	2.40
	Blind people get a truer first impression of others than most people do.	.46	-1.93	2.39
	People with heart trouble feel sorry for themselves.	.61	-.81	1.42
	Children with heart trouble are usually more friendly than other children.	.18	-1.10	1.28

Table 12

Correlation Coefficients for Factor Scores

	FSMED1	FSMED2	FSUN1	FSUN2	FCON1	FCON2
FSMED1	1.0000	.0000	.8729	.2861	.7330	.4564
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .	P= .500	P= .000	P= .009	P= .000	P= .000
FSMED2	.0000	1.0000	-.1074	.7777	.0368	.5665
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .500	P= .	P= .190	P= .000	P= .382	P= .000
FSUN1	.8729	-.1074	1.0000	.0000	.7246	.3453
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .000	P= .190	P= .	P= .500	P= .000	P= .002
FSUN2	.2861	.7777	.0000	1.0000	.1794	.6575
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .009	P= .000	P= .500	P= .	P= .070	P= .000
FCON1	.7330	.0368	.7246	.1794	1.0000	.0000
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .000	P= .382	P= .000	P= .070	P= .	P= .500
FCON2	.4564	.5665	.3453	.6575	.0000	1.0000
	(69)	(69)	(69)	(69)	(69)	(69)
	P= .000	P= .000	P= .002	P= .000	P= .500	P= .

Figure 1

Unmarked Graphic Scale

For each statement place a mark on the line beneath it indicating how strongly you agree or diagree.

EXAMPLE:

People with cancer ought to be kept apart from the normal community.

(In this example, the person strongly disagreed with the statement.)

Figure 2

Principal Components Analysis - Two Factors - Mediated

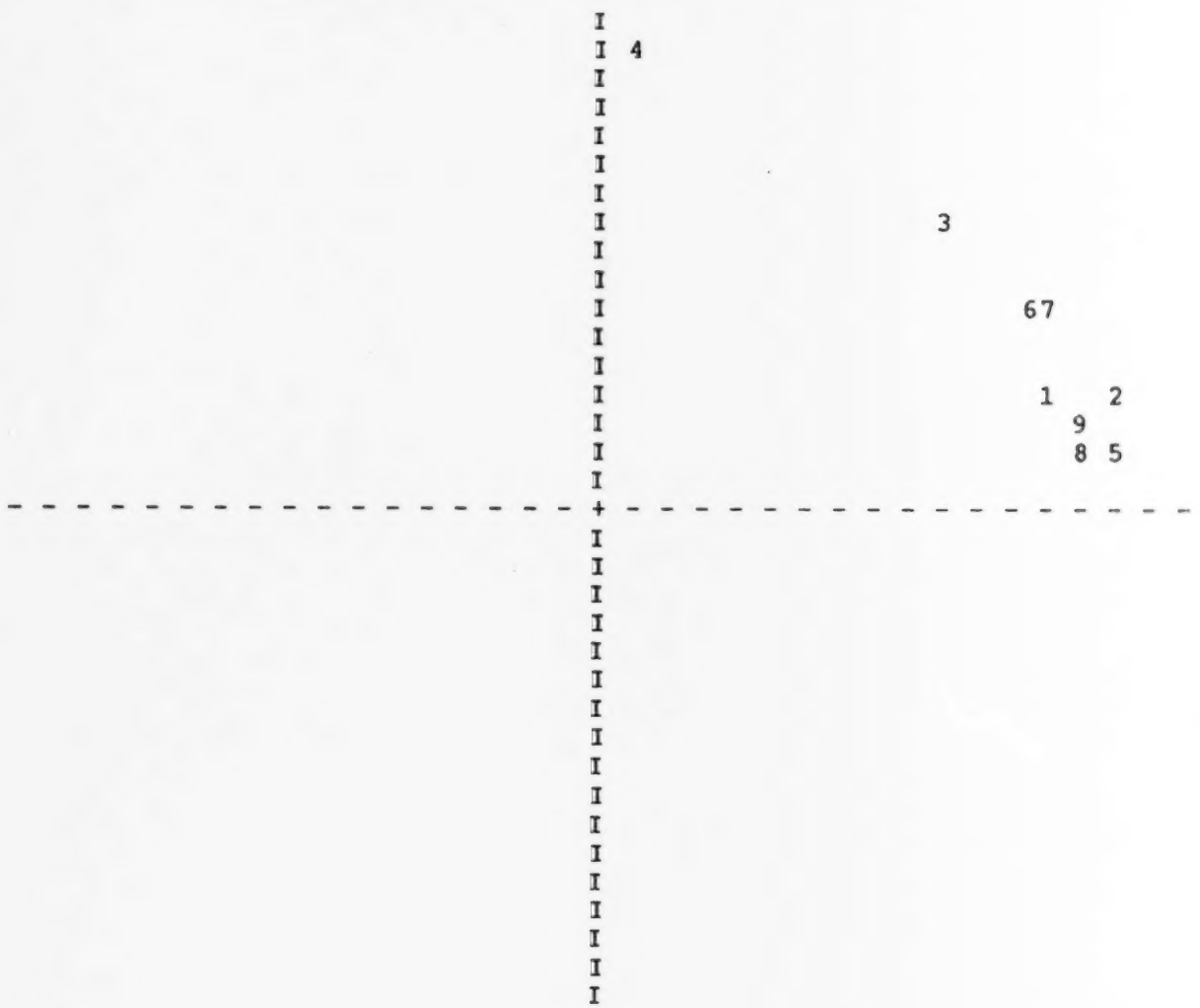

Figure 3

Principal Components Analysis - Two Factors - Unmarked

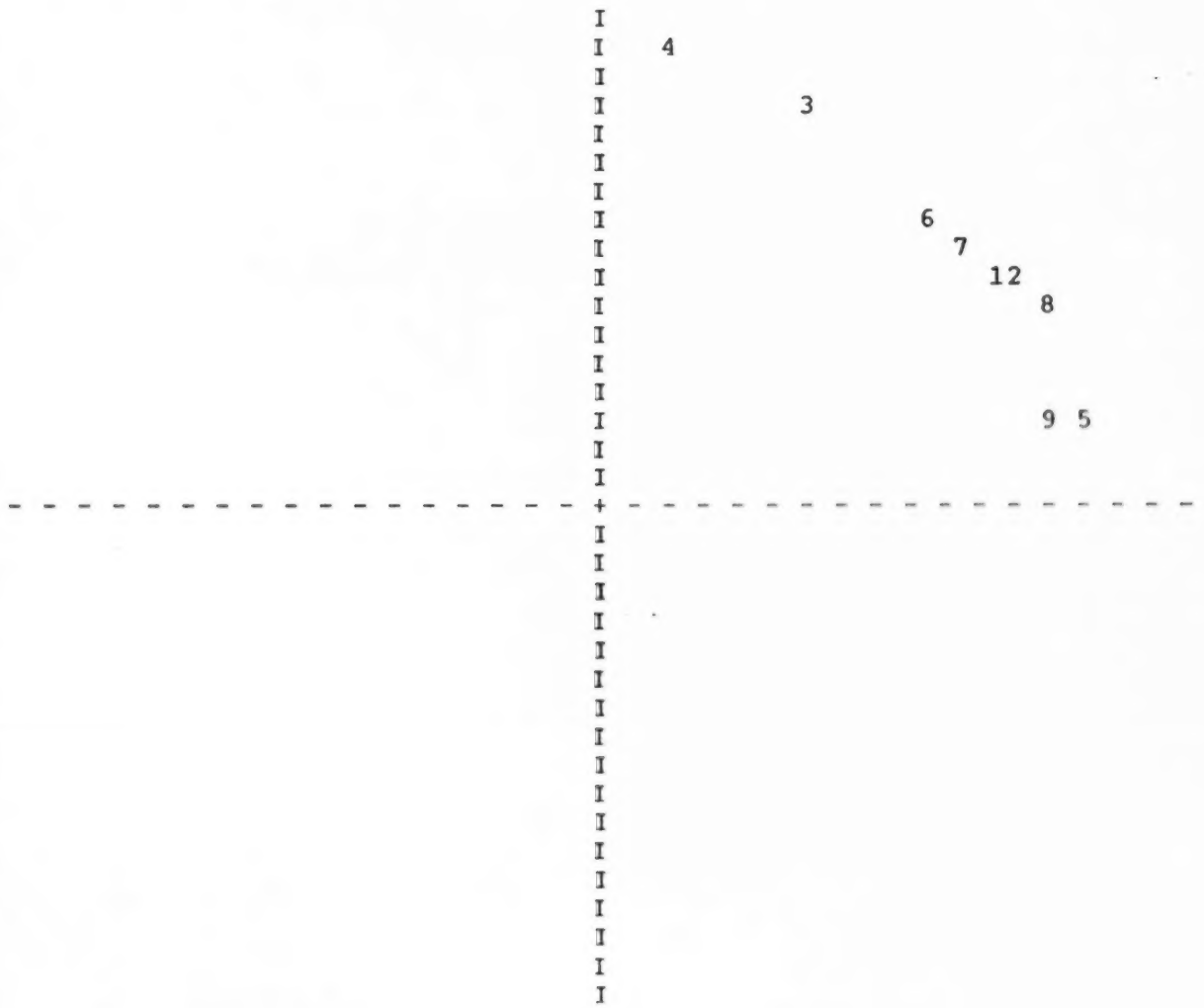

Figure 4

Principal Components Analysis - Two Factors - Conventional